during machine milking in dairy ewes

S. Casu[1], A. Carta[1], C. Robert-Granié[2]

[1] Istituto Zootecnico e Caseario per la Sardegna, Olmedo (Sassari), Italy.
[2] Station d'Amélioration Génétique des Animaux, INRA, France.

RIASSUNTO – Modellizzazione della cinetica di emissione del latte alla mungitura meccanica degli ovini – *Il presente lavoro riguarda la modellizzazione della curva d'emissione del latte, a partire da 12 misure eseguite automaticamente durante la mungitura meccanica di 852 pecore primipare, controllate ogni 15 giorni. L'adozione della tecnica dei polinomi frazionari ha consentito di trovare un polinomio di secondo grado che permettere di descrivere tale emissione in funzione del tempo di mungitura sia a livello medio che a livello individuale.*

KEY WORDS: milk emission, fractional polynomials, random regression

INTRODUCTION – The individual milking time is one of the aspects which affect the routine of milking in dairy ewes and the time to devote to this laborious task. The positive effect of an appropriate udder conformation in the reduction of manual interventions (stripping) during milking, have been clarified by numerous studies (Marie-Etancelin *et al.*, 2001), leading to the development of appraisal methods of the udder which are being implemented in several breeding programs to improve udder morphology for milkability. On the other hand, a lack of knowledge on kinetics of the milk emission during machine milking still persists, mainly as a consequence of the difficulty of a large scale recording. Recently an automatic device able to follow individual kinetics of milk emission, developed by INRA (Ricard *et al.*, 1995), was installed at the IZCS. The first purpose of this work was modelling the average shape of milk emission curves during machine milking by fitting an appropriate polynomial. Furthermore, since previous analysis showed that milk flow parameters, such as maximum or average milk flow, manifested an individual variability (Carta *et al.*, 2000), it was investigated whether this variability is also present in the shape of individual curves. With this goal a linear mixed model with random regression coefficients was implemented.

MATERIAL AND METHODS – In 2000 a flock of backcross Sarda*Lacaune primiparous ewes was fortnightly recorded for the kinetics of milk emission. Only the morning records pertaining to the 2-milkings/day period were considered (no.=4927) and only animals with at least 3 recorded kinetics were retained (no.=852). The automatic INRA device stores 12 intermediate measurements of milk at prefixed lag, which was set to 8 s at the beginning of lactation and 6 s at the end. The variable analysed as a function of time was the milk recorded at each lag, starting after the time needed to collect the first 160 ml of milk in the jar (T_0=0). The factors affecting the milk emission curve were: the management group (G, 5 groups homogenous for stage of lactation), the milker (M), and the TD. In order to adjust for intra-mammary pressure, a further factor taking into account the degree of udder filling was considered on the basis of the ratio between the milk produced at the recorded milking and the maximum milk yield ever produced by the animal (F, 3 classes). The choice of the function of time (f(t)) to model the shape of milk emission curve followed 2 steps. In the first step, the (f(t)) for the fixed part of the model was chosen. The search for the optimal f(t) was extended to the fractional polynomials (FP), which are an extension of conventional polynomials but with real powers (Royston and Altman, 1994). Let t be a positive real covariable, $\boldsymbol{p}$={p_j}, j=0 to m a (m+1) vector of ordered powers and $\boldsymbol{\xi}$ ={ ξ_j} the vector of the corresponding real coefficients. A FP of degree m is defined as follow: ϕ_m $(t, \xi : \boldsymbol{p}) = \sum^m_{J=0} \xi_j$ H_j (t) where H_j $(t) = t^{(pj)}$ if $p_j \neq p_{j-1}$ and $H_j(t) = H_{j-1}(t)*ln(t)$ if $p_j = p_{j-1}$. In the last formula $t^{(pj)}$ represents the Box-Tidwell transformation, i.e. $t^{(pj)} = t^{pj}$ if $p_j \neq 0$ and $t^{(pj)}=ln(t)$ if $p_j = 0$. At the origin H_0 $(t) = 1$. Thus for m = 2, four different families of polynomials can be found (Table 1). The set of the best combinations of possible real powers for functions FP2, FP3, FP4, was found by least squares method for nonlinear models, applied to data adjusted for the interaction G*M*F*TD (129 levels) and the individual random effect. Afterwards, the FP with the selected powers, as well as the cubic and Ali-Schaeffer functions (Ali and Schaeffer, 1987) were introduced, within each level of G*M*F*TD interaction (Table 1), in a mixed model, also including the random individual effect. Models were compared on the basis of the AIC. In the second step, in order to explore the individual variability of milk emission curves, the technique of random regression (RR, Schaeffer and Dekkers, 1994), in which individual coefficients are random variables with a covariance matrix, was applied, to take into account the correlation structure among repeated observations on each individual. A first and second order conventional polynomials and the same function chosen for the fixed part of the model were considered.

Table 1. Analysed functions, selected powers and AIC for different models.

	Function	Selected powers	AIC
FP1	$a_0+a_1ln(t)+a_2ln(t)^2$	-	-350931
FP2	$a_0+a_1ln(t)+a_2t^{b1}$	b_1=-0.3	-351442
FP3	$a_0+a_1t^{b1}+a_2t^{b1}ln(t)$	b_1=1.0165	-349628
FP4	$a_0+a_1t^{b1}+a_2t^{b2}$	b_1=-.28 ;b_2=-.29	-
Cub	$a_0+a_1u+a_2v+a_3u^2+a_3v^2$	-	-349104
AS*	$a_0+a_1t^1+a_2t^2+a_3t^3$	-	-348929

u=t/10; v=ln(10/t).

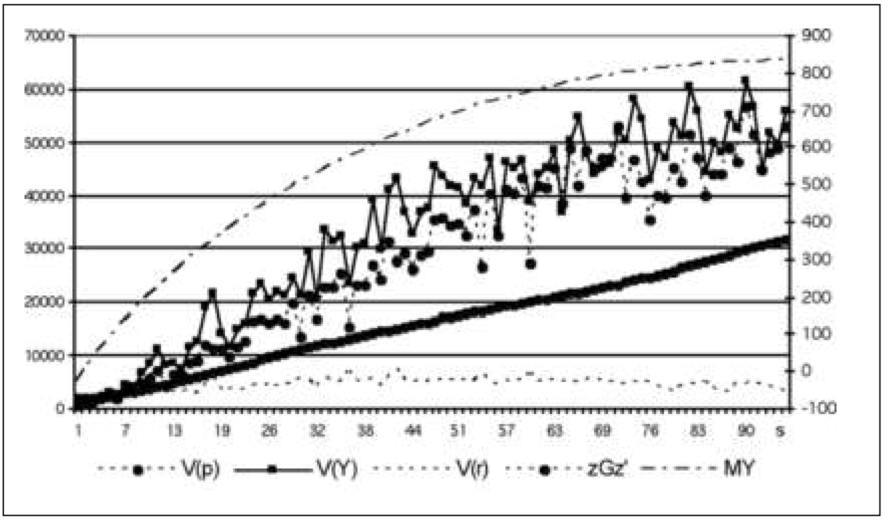
RESULTS AND CONCLUSIONS – Table 1 shows the estimates of powers for FP2, FP3, FP4. Estimates of b1 and b2 for FP4 were very similar, this leading, for the theory of FP, to the same function as FP3. Thus FP4 was no more investigated. Among the others FP, the FP3 was the best on the basis of the AIC. Although FP3 shows a lower AIC than the Cub and AS functions, it allows a similar fitting of data, but with less parameters and thus it was chosen to fit the fixed part of the model. Furthermore, in the RR model, FP3 fitted the individual component better than the linear and quadratic polynomials, on the basis of –2logL and AIC. Values of variance and covariances estimates for the random coefficients of the complete selected model (tables 2), in which residual variance was estimated to 4418, indicate an high individual variability of the milk emission curves.

Table 2. Variance-covariance matrix of the FP3 regression coefficients (G).

	a_0	a_1	a_2
a_0	1842.41	-127.13	16.49
a_1	-127.13	124.13	-24.57
a_2	16.49	-24.57	5.02

In order to illustrate the typical shape of these curves, the estimate of FP3 for one level of G*M*F*TD interaction is reported in Fig. 1. In longitudinal data analysis not only it is crucial to model the systematic pattern of the trait along time but also to accurately describe the trend of variances. The figure shows that the increasing variability of successive measurements of milk yield (V(Y), V(P)) is taken into account by the G as shown by the trend of individual estimated variance. This leads to an almost homogeneous residual variance, as proved by trend of the empirical variance of residuals. In conclusion, the technique of fractional polynomials seems flexible and parsimonious to fit the curve of milk emission.

Figure 1. Milk emission curve (MY) and evolution along time of observations (Y), predicted (P), individual (zGz') and empirical residual (r) variances.



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